STUDY OF ADAPTIVE FILTERS FOR BIOMEDICAL APPLICATIONS

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Abstract

Adaptive filters are a special class of digital filters, whose characteristics can be modified automatically without the need for intervention by the user. For many applications of the adaptive filtering, the Least Mean Square (LMS) criterion is useful. The LMS algorithm is simple to implement.

In biomedical signal acquisition like Electrocardiography ECG or Electroencephalography EEG one of the main problems is to separate the small input signals from noise and disturbances caused by the 50Hz power supplies, high frequency interference and random body voltages. Adaptive filter techniques are required to overcome this problem. Different adaptive filter types have been analyzed. Finite Impulse Response (FIR) filters are preferred because of their better stability. An adaptive filter was implemented which suppresses known noise sources in an ECG application. Simulations were done with MATLAB A 50 Hz interference on the ECG input signal was attenuated by 50 dB. The convergence time for the adaptive algorithm was less than 3 sec. The filter implementation needed 9500 equivalent gates and worked with 7.2 µW for a filter clock speed of 1.6 kHz. This paper aims to help to reduce the noise interference in the ECG signals and better diagnose results. Some of the most common examples of noise that the ECG filter would need to remove in order to give useful results includes power line interference, motion artifacts, muscle contraction, electrode contact noise and interference caused due other electronic equipment. ECG signals are weak and easily susceptible to noise and interference

In this research work, the LMS algorithm is implemented using MATLAB software and some and biomedical applications are studied.

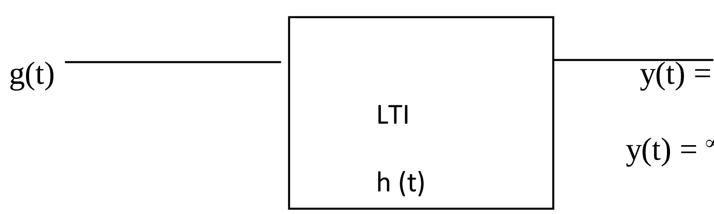
Keywords:- Adaptive filters, LMS algorithm, FIR Filters, ECG, MATLAB etc.

I. INTRODUCTION

A. Digital filters :

Digital Signal Processing is an area of science and engineering that has developed rapidly over the last 40 years. Digital Signal Processing is the processing of signals by digital means. One of the most widely used complex signal processing operation is digital filtering. Filtering is used to pass certain frequency components in a signal through the system without any distortion and to block other frequency components. The system implementing this operation is called filter.

Various filters are defined, depending on the nature of the filtering operation. The operation for the liner system is linear and is described by the convolution integral.



$$y(t) = h(t) * g(t)$$

$$y(t) = {}^{\infty}\!\int_{\infty} h(t-\tau)\, g(\tau)\, d\tau$$

where ,

g (t) is the input signal

y (t) is the output of the filter characterized by the impulse response h(t).

A linear system with frequency response H(w) acts as a filter to signals of different frequencies at input. Filters are usually classified according to their frequency- domain characteristics as Low pass, High pass, Band pass and Band stop or Band elimination filters.

In general digital filters are
IIR [Infinite Impulse Response] filters
FIR [Finite Impulse Response] filters.

B. IIR [Infinite- Impulse Response] filters:

IIR filters are characterized by infinite duration impulse responses. Some of these impulse responses can be modeled by rational system functions or, equivalently, by difference equations. Such filters are termed as auto- regressive moving average (ARMS) or, more generally, as recursive filters. Those IIR filters that cannot be so modeled are called non recursive filters. In DSP, IIR filters generally imply recursive ones because these can be implemented efficiently. Therefore we will always use the term IIR to imply recursive filters.

Since our filters are LTI systems. We need the following three elements to describe digital filters structures.

These elements are
1) Adder
2) Multiplier (gain)
3) Delay element (shifter or memory)

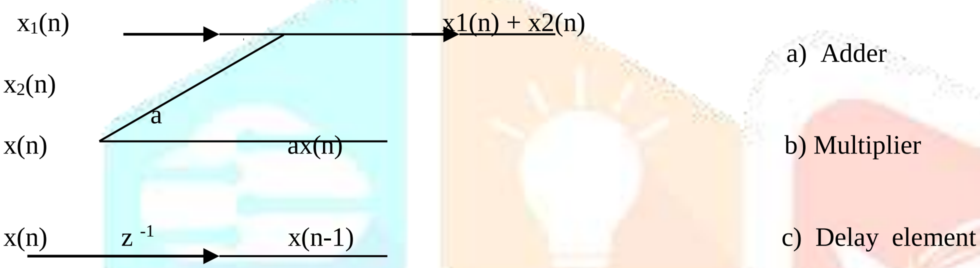


fig. 1 Three basic element

The difference equation representation of an IIR filter is expressed as

$$y(n) = \sum_{m=0}^{M} b_m \, x(n-m) - \sum_{m=1}^{N} a_m \, y(n-m)$$

To implement an IIR filter five different structures can be used:

a) Direct form Structures
b) Cascade Structures
c) Parallel Structures
d) Lattice Structures
e) Lattice -ladder Structures

C. FIR [Finite- Impulse Response] filters :

FIR filters are characterized by finite -duration impulse responses. ARMA filters include moving average filters that are FIR filters. FIR filters and IIR filters are linear time-invariant (LTI) systems that can recreate a large range of different frequency responses.

A FIR filter has a system function of the form

$$H(z) = b_0 + b_1 z^{-1} + \ldots + b_{M-1} z^{1-M}$$

$$H(z) = \sum_{n=0}^{M-1} bn \, z^{-n} \quad \ldots (A)$$

Hence the impulse response h (n) is

$$h(n)= \begin{cases} b(n), & 0 \le n \le M-1 \\ 0, & \text{else} \end{cases} \qquad \text{……….. (B)}$$

The difference equation representation is

$$y(n)=b_0x(n)+b_1x(n-1)+\ldots\ldots+b_{M-1x}(n-M+1) \qquad \text{……..(C)}$$

Which is a linear convolution of the finite support .

The FIR filter structures are always stable, and they are relatively simple compared to IIR filter structures. FIR filters can be designed to have a linear phase- response, which is desirable in some applications.

A FIR filter is a filter structure that can be used to implement almost any sort of frequency response digitally. An FIR filter is usually implemented by using a series of delays, multipliers and adder to create the filter's output.

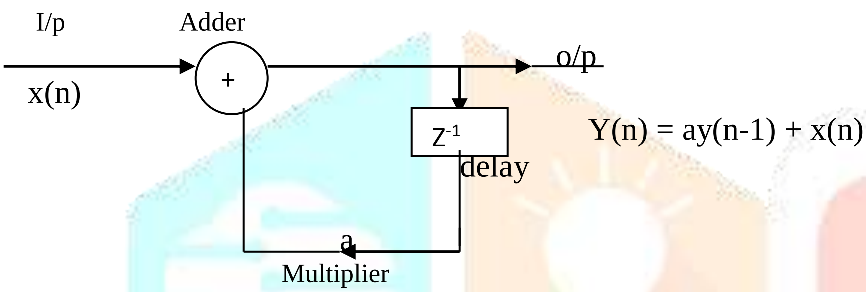


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Fig 2. First order recursive filter

Fig 2. Shows the basic block diagram for an FIR filter of length N .

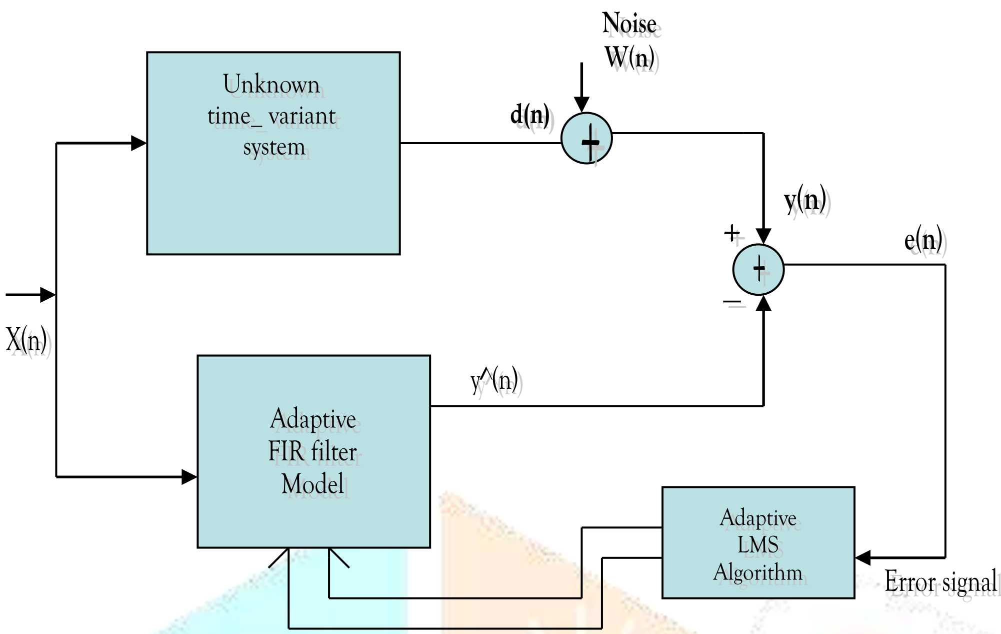
The delays result in operating an prior input samples. The hk values are the coefficients used for multiplication, so that output at time n is the summation of all the delayed samples multiplied by the appropriated coefficients.

The output of a filter Y(n) is expressed in the form of a differential equation.

$$Y(n) = x(n) + ay(n-1)$$

The first order recursive filter shown in figure 2.

D. Adaptive Filters:



Adaptive filters are a special class of digital filters.

An adaptive filter is very generally defined as a filter whose characteristics can be modified to achieve some end or objective, and is usually assumed to accomplish this modification (or "adaptation") automatically, without the need for substantial intervention by the user. While not necessarily required it is also usually assumed that the time scale of the modification is very slow compared to the bandwidth of the signal being filtered. Implicit, in this assumption is that the system designer could (over any particular substantial time window) in fact use a time- invariant, non adaptive filter if only the designer know enough about the input signals to design the filter before its use.

This lack of knowledge may spring from true uncertainty about the characteristics of the signal when the filter is turned on, or because the characteristics of the input signal can slowly change during the filter's operation. Lacking this knowledge, the designer then turns to an" adaptive" filter, which can "learn "the signal characteristics when first turned on and thereafter can "track "slow changes in this characteristics.

In this way, the goal of an adaptive filter is to "find and track "the optimum filter corresponding to the same signal operating environment with complete knowledge of the required statistics.

Adaptive filters have received considerable attention from researchers over the last 25 years. As a result, many computational efficient algorithms for adaptive filtering have been developed.

The analysis and design of three basic classes of adaptive filters are

1) Adaptive Finite-Impulse-Response (FIR) filters
2) Adaptive- Infinite-Impulse-Response (IIR) filters
3) Adaptive Property – Rest oral filters.

Although both IIR and FIR filters have been considered for adaptive filtering, the FIR filter is by far the most practical and widely used .The reason for this preference is quite simple .The FIR filter has only adjustable zeros, and hence it is free of stability problems associated with adaptive IIR filters that have adjustable poles as well as zeros.

Adaptive FIR filters are always stable. On the contrary, the stability of the filter depends critically on the algorithm for adjusting its coefficients.

So, for implementation of the adaptive filters two basic algorithms:

the Least –Mean-Square(LMS) algorithm ,which is based on a gradient optimization for determining the coefficients , and the class of recursive least – squares (RLS) algorithm is used.

The LMS Algorithm, introduced by Widrow and Hoff (1960), is widely used in practice due to its simplicity, computational efficiency and good performance under a variety of conditions.

The basic algorithm, called the Least-Mean- Square (LMS) algorithm, to adaptively adjust the coefficients of an FIR filter. The adaptive filter structure that will be implemented is the direct form FIR filter structure with adjustable coefficients h(0) , h(1) ,…, h(N-1).

The least squares (and MSE) criterion provides a good measures of performance in adaptive filtering applications.

E. Biomedical signal Processing: In many applications for biomedical signal-processing the information-bearing signals are superposed by further components. Thus signals get distorted and the extraction of information is complicated. In electrocardiography interferences may have a technical source, for example a power supply unit, or a biological source, for example respiration. Commonly frequency-selective filters with fixed coefficients are used to suppress a specific frequency range of a signal. If the frequency spectrum of signal and interference overlap or the characteristic of the interference is time dependent or not exactly known, filters with fixed coefficients can hardly meet the demands. Often the filter's transfer behavior can't be specified sufficiently exact or those spectral of the ECG which falls in the filter's cut-off region get lost.

III RELATED WORK

Measurement of Biological activity by means of monitoring electrical discharge, as typified by the monitoring of heart patients, parallel the communications problem: A transmitter (the electrical discharge) radiates energy through a propagation path (the body's tissue) to a receiving antenna.(an electrode) positioned to maximize energy reception. Because the electrical discharge involves very small potential, the received signal is very weak and requires care to prevent degradation of the signal content by added noises or filtering. Probably the strongest source of interference is 50/60 Hz. Pickup and its harmonics emanating from nearby electrical equipment such as lightening and instrument power supplies.

The conventional means for dealing with such strong, spectrally concentrated interference is a fixed, low pass filter which scarifies waveform details associated with spectral components above 50 Hz.

Use of a Notch filter suppressing the energy in the appropriate narrow spectral band represents an improvement; however it still distorts the signal component of interest.

The hum remover uses an adaptive filter to produce an estimate of an interfering signal and then subtract it away from the corrupted signal of interest.

The fig 3 shows the block diag. of the Adaptive Noise Canceller (ANC)

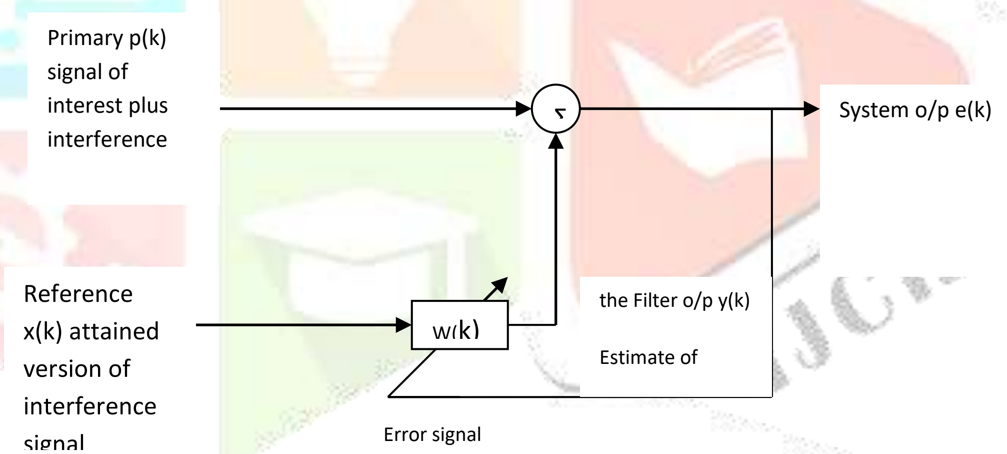


Fig 3. Block diagram of the adaptive noise canceller.

It has two inputs and a single output. The primary input p(k) contains the signal of interest plus one or more interfering signals . The second input, termed the reference input x(k), is applied to the input of the adaptive filer. This reference input should be as rich as possible in the signals interfering with the signal of interest and should contain as little of the single of interest as possible.

The objective in adapting the coefficients of the filter is to produce a filter output y(k) that matches , the exact waveform of the interference signals appearing in the primary input . The filter output is subtracted from the primary input to produce the system output e(k). If the filter can be adjusted to achieve a perfect match between filter output y(k) and the interference present in the primary signal p(k), then e(k) , the system output , contains only the signal of interest . To the extent that the filter cannot be so adjusted, then a certain amount of the interference remains.

Note that the ANC uses the system output e(k) as the error signal to drive the filter's adaptation. When the filter's coefficients are optimally adjusted, the presence of the interference in the error is minimized. By using a adaptive algorithm that minimizes the presence of the interference, the best coefficients can be found. The primary signal is that provided by the medical instrumentation containing both the ECG signal of interest and the 50/60 Hz. interfering signal component received from the room's power system.

The reference input x(k) is obtained from the power mains themselves, thus being reach in the interference signal and containing very little of the medical signal of interest. The difference signal e(k) is both the system output and error signal used to drive the filers adaptive algorithm. The ANC is widely used in practice. While the full range of designed possibilities are available in terms of filter structure, performance functions, and adaptive algorithm, the most common designs use FIR filters, least- squares performance criterion and the LMS approximate- gradient -descent adaptive algorithm.
The LMS algorithm provides as alternative computational method for determining the optimum filter coefficients {h(k)} without explicitly computing the correlation sequences $\{r_{xx(k)\}}$ and $\{r_{dx}\}$. Algorithms for recursively computing the filter coefficients and, thus, searching for the minimum of E_M, have the form

$h_M(n+1) = h_M(n) + 1/2\ \Delta(n)\ S(n)$,n=0,1,…. ………(1)

Where ,
$h_M(n)$ is the vector of the filter coefficients at the nth iteration,
$\Delta(n)$ is the step size at the n_{th} iteration.
S(n) is the direction vector for the n_{th} iteration.
The initial vector $h_M(0)$ is chosen arbitrarily.

Considering the search methods based on the use of gradient vectors.
The simplest method for finding the minimization of EM recursively is based on a steepest decent search.
In this method of steepest descent, the direction vector S(n)=-g(n),where g(n) is the gradient vector at the nth iteration, defined as

$g(n)= d\, E_M(n)/d\, h_M(n)$ …….(2)

The recursive algorithm based on the method of steepest decent is
$h_M(n+1) = h_M(n) - 1/2\ \Delta(n)\ g(n)$ ………(3)

The algorithm leads to convergence of $h_M(n)$ to h_{opt} in the limit as n ∞’ provided that the sequence of the step sizes Δ(n) is absolutely summable , with Δ(n) 0 as n- ∞ It follows that as n-∞.g(n)-0.

An unbiased estimate of the gradient vector at the nth iteration is given as
$g\hat{}(n)= -2e(n)\ X^*_{M(n)}$ ……….(4)
thus , g^(n) substituted for g(n)-0, we have the algorithm
$h_M(n+1) = h_M(n) + \Delta(n)\ e(n)\ X^*_{M(n)}$ ………(5)
This is called a stochastic–gradient-descent algorithm, it has a variable step-size.

In adaptive filtering a fixed step- size-size algorithm is use:
For two reason
The first is that a fixed step size algorithm is easily implemented in either hardware or software.
The second is that a fixed step size is appro0priate for tracking time –variant signal statistics, where as if Δ(n)- 0 as n- 0
For this reason, eq(2.5.8) is modified to the algorithm.

$h_M(n+1) = h_M(n) + \Delta e(n)\ X^*_{M(n)}$
Where ,
Δ is now fixed step-size .
This Algorithm was first proposed by Widrow and Hoff (1960), and is now widely known as the LMS (Least Mean Squares) algorithm .
Cleary, it is a stochastic–gradient algorithm.

IV. RESULTS AND DISCUSSION

The ECG of an healthy adult has a fundamental frequency from about 70 bpm[5] up to 80 bpm. For certain disease patterns fundamental frequencies down to 20 bpm occure. At physical stress frequencies up to 200 bpm are observed. The adaptive filter was tested for ECG signals with different fundamental frequencies. For frequencies up to 160 bpm good results were achieved, whereas the signal quality is downgrading for higher frequencies. Furthermore the filter was applied to ECGs with a power line interference of different frequencies. For interfering frequencies from 30 Hz to 100 Hz the filter turned out to be well suitable. The influence of the amplitude of the superposed signal was also studied. Interfering components with amplitudes from 0,05% to 100% relating to the maximum ECG amplitude can be extracted. Depending on the amplitude of the superposed signal, the interference was damped by 4 dB up to 50 dB. Convergence time of the adaptive algorithm is less than 3 sec. For a VIRTEX E FPGA [3] from Xilinx the filter realization needs 9500 equivalent gates and the calculated power loss is 7.1 µW . Using a sampling frequency of 256 Hz for the ECG the filter clock speed is 1.8 kHz.

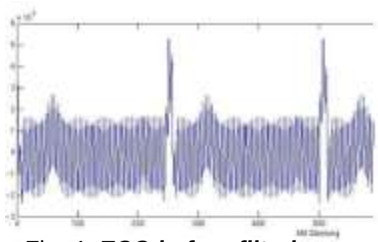


Fig. 4 ***ECG before filtering***

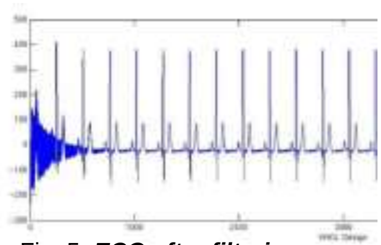


Fig. 5. ***ECG after filtering***

Using MATLAB Tools, the results are computed. The noisy ECG signal which is taken as input is filtered using adaptive filter algorithms LMS. The original ECG signal is passed through the LMS adaptive algorithms and hence improving the SNR ratio of the signal to a greater extent.

V. CONCLUSION

This paper shows the simplicity of LMS algorithm and ease of implementation, evident from above make this algorithm better in many real time systems to improve the SNR and to reduce the noise of signal. Information of fetal heart rate, derived from the fetal ECG, is valuable in assessing the condition of the baby before or during birth of a baby. Adaptive filter have been used to derive a noise free fetal electrocardiogram signal.

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